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The Effects of Platform Design on Solar PV Prices in an Online Marketplace

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The Effects of Platform Design on Solar PV Prices in an Online Marketplace

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Report

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Master of Science in Engineering

The University of Texas at Austin

December 2017

Acknowledgements

The report was written under the supervision of Dr. Benjamin Leibowicz. I would like to thank him for his continuous guidance throughout the project. This project was completed in collaboration with National Renewable Energy Limited (NREL). I wish to thank Eric O'Shaughnessy and Robert Margolis from NREL, for providing the initial analysis and for contributing to the introduction and quote platform design sections. I would specially like to thank EnergySage for their collaboration on this project and for providing us with information on their platform design and for providing us with the relevant dataset.

Abstract

The Effects of Platform Design on Solar PV Prices in an Online Marketplace

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Adoption of rooftop solar PV is hindered by lack of transparency about cost, equipment quality and government incentives. Third party quote aggregator platforms have the potential to influence both the consumers as well as installers and reduce overall costs by increasing the competition among installers. Our major findings focus on platform design and auction rules set by the quote aggregator and how this platform design impacts quote prices. We build a linear regression model with quote price as a dependent variable and competition and system related characteristics as explanatory variables. We use a regression discontinuity approach to study the impacts of four platform design changes on quote prices and transaction prices. We find that *price reference* provided to installers has the most significant impact on quote prices, as it lowers the quote prices by 0.10 \$/W, by acting as an anchor. Our results show that premium quality panels cost 0.48 \$/W more than the economy panels, thus premium panels are significantly associated with higher priced quotes. Further, we focus on valuation of panel quality to see if an online marketplace auction triggers a race to the bottom, sacrificing quality. We find that customers value the

premium panels at a greater price than what the installers are offering. Customers on an average pay 0.12 $/W more for a premium panel, than what the installers are quoting.

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Chapter 1: Introduction

The vast majority of residential solar photovoltaic (PV) customers in the United States procure PV by obtaining price quotes directly from PV installation companies (Mond 2017). More recently, customers are increasingly obtaining quotes through third-party quote platforms, where a third-party quote aggregator obtains quotes on behalf of prospective customers (Mond 2017). Quote platforms and other market innovations could fundamentally change how prospective customers navigate the PV adoption process (O'Shaughnessy and Margolis 2017). In this study, we explore how quote platform design affects price quotes offered by installers as well as transaction prices actually paid by purchasing customers.

Quote aggregation platforms allow customers to relatively easily obtain quotes from multiple installers. Customers create an account with the quote aggregator and provide basic home information to allow installers to develop site-specific quotes (e.g., address, electricity demand, preferences about equipment attributes). The quote aggregator conveys this customer information to a network of PV installers. Interested installers then develop quotes including a quote price, system size, and other system specifications, and submit quotes to an online quote platform. The customer is then able to compare all submitted quotes on the platform.

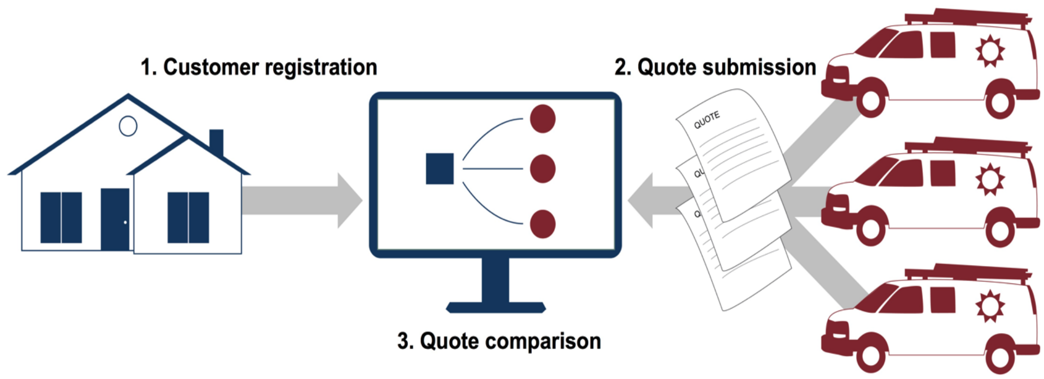

Figure 1.1: Quote aggregation platforms

Quote platforms can be modeled as a type of multi-dimensional auction where customers compare products from multiple bidders (installers) along dimensions of price and product attributes (e.g., system size, module brand) and select the product that provides the greatest net value. Alternatively, the customers may decide not to accept any quotes, i.e., select none of the available products. The robust literature of auction theory shows that auction *design* plays a critical role in auction outcomes (Che 1993; Klemperer 2002; Myerson 1981; McAfee and McMillan 1987). Certain auction designs favor customers while other designs favor bidders. In the context of quote platforms, it is likewise possible that certain quote platform designs favor prospective PV customers while other designs favor installers. Prices on quote platforms may reflect the degree to which platform design favors one party or the other; lower prices provide evidence of program designs that favor customers, all else equal.

The objective of this study is to determine the degree to which quote platform design affects prices on quote platforms. Using quote data provided by the U.S. quote aggregator EnergySage (EnergySage website), we study how quote platform prices changed due to four design changes made on EnergySage's quote platform. Chapter 2 summarizes quote platform design and the four design changes in our study. Chapter 3 summarizes our data and methods. Chapter 4 provides results, and Chapter 5 concludes the report.

Chapter 2: Quote Platform Design

Quote platforms may vary along a number of dimensions (Figure 2.1). For simplicity, we break quote platform design into three information flows:

- The *installer information flow* refers to the information that the aggregator requires from customers and provides to installers. This information flow may include other relevant market information like the number of other installers active in the customer's market or average prices in the area.
- The *customer information flow* refers to the information that the aggregator requires from installers and provides to customers. This flow includes all information that installers must provide in quotes to be able to post quotes to the platform. This flow may include other relevant market information such as average prices in the customer's area.
- The *open communication* channel refers to any open communication between the customer and the installer, which may or may not be mediated by the aggregator.

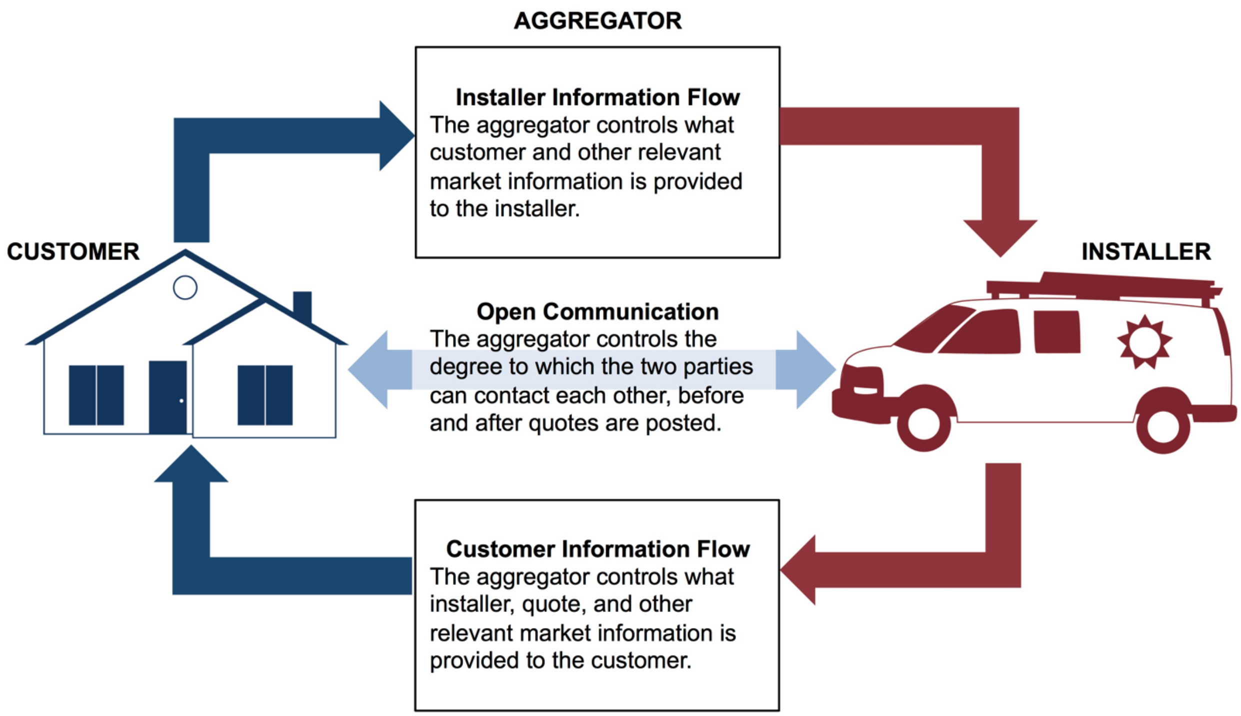

Figure 2.1: Quote platform design elements

2.1 Platform design and PV customer outcomes

In general, designs that optimize customer information flows should improve customer outcomes. *Optimization* in this context does not imply maximization. One of the benefits of quote platforms is their ability to restrict the flow of superfluous information. Individual installers may provide different levels of detail in their quotes and installers may use different formats when presenting quotes to customers. In providing quotes directly to customers, installers may employ various sales tactics to promote the installer brand or reputation that do not necessarily convey meaningful information about the quoted system. On quote platforms, customers can compare multiple quotes conveying the same level of detail in a common format. An optimized design provides the minimum amount of information necessary for customers to make an informed decision and restricts superfluous information that may serve to confuse customers. An optimal customer information flow may include system information (e.g., size, module brand), installer information (e.g., years of experience, certifications), and market information (e.g., average prices in the customer's market).

Similarly, designs that optimize installer information flows should improve customer outcomes. At a minimum, installers need enough customer site-specific information to be able to develop an accurate cost estimate. Excessive restrictions on installer information flows could result in inaccurate quotes that may need to be adjusted in subsequent stages of the adoption process. At the same time, quote platforms can restrict installer information flows for superfluous information that may reveal the customer's valuation of solar. For instance, installers may be able to use information about customer electricity usage to mark-up or discount prices according to the potential benefits that customers would accrue from solar adoption, a practice known as value-based pricing (Barbose et al. 2015; Gillingham et al. 2016). Certain restrictions on installer information flows may improve customer outcomes by limiting the ability of installers to offer value-based prices.

The effects of open communication are more nuanced. Open communication may allow customers to better communicate idiosyncratic demands to installers, and may allow installers to better signal the differentiated qualities of their services. Further, open communication allows both parties to obtain further information that is either excluded from or overly vague on the quote platform. At the same time, open communication may increase customer vulnerability to conventional sales tactics and value-based pricing, especially if open communication is allowed before quotes are posted to the platform. Aggregators can restrict open communication by masking customer and installer identities to varying degrees. For instance, the aggregator may withhold all contact information about both parties but allow each party to communicate via messaging on the quote platform.

2.2 Design Changes on the EnergySage Quote Platform

For proprietary reasons, an in-depth description of the design of EnergySage's quote platform will not be provided. However, for the purposes of this study, EnergySage described four design changes that the aggregator has implemented since 2016, summarized in Table 2.1.

Design change	Date	Type	Description
Customer map	May 2016	Customer information flow	Upon registration, customers are able to view a map showing the location of other customers in the area that have obtained quotes on the platform
Quote cap	July 2016	Customer information flow	The maximum number of quotes received by each customer is capped at seven
Price reference	March 2017	Installer information flow	Installers are provided information about competitive prices in the customer's market before submitting a quote
No pre-quote messaging	June 2017	Open communication	Installers are prohibited from sending messages to customers before posting a quote to the platform

Table 2.1. EnergySage Quote Platform Design Changes

Based on the literature, we have expectations about some of the design changes on customer outcomes, while the literature is less informative about others. We study the current literature for the possible effects of these design changes and present the results below.

2.2.1 Customer map

Since May 2016, customers are shown a map during the registration process. It shows the location of other customers in the area that have obtained quotes on the platform.

Social interaction and adoption by neighbors plays a key role in diffusion of new technologies and same is the case for solar PV adoption. According to Rogers (2010), diffusion of new technologies is fundamentally a social process. Studies show that adoption of solar PV is positively affected by the presence of neighbors who have already adopted it (Noll, Dawes, & Rai 2014; Rai, Reeves, & Margolis 2016). Bollinger and Gillingham (2012) find that an additional solar PV installation increases the probability of adoption in that zip code by 0.78 percentage points. In an online marketplace, it may not be possible for the customers to interact among themselves or gauge the status of adoption of technologies by their physical neighbors, but a feature like customer map can aid the adoption process by enabling virtual peer effects. Similar studies have been performed on diffusion of other sustainable technologies, like hybrid cars. For example, in a recent study among Irish households, a model of innovation diffusion is developed to simulate the adoption of electric vehicles. It is found that even if overall adoption is relatively low, mild peer effects could result in large clusters of adopters forming in certain areas (McCoy and Lyons 2014). Ozaki and Sevastyanova (2011) show similar results with a case study on consumer adoption of hybrid vehicles. They show that social norms and consumers' willingness to comply with the norms of their groups influence the purchase decision of customers. McShane et al. (2012) in their research show how customers are more likely to purchase a new car due to the peer effects and how these effects are moderated by the visibility of adoption. They show that visual effects are present and are larger in the areas where other's behavior is more visible.

Thus, an introduction of customer map for the customers visiting the EnergySage website can be seen as a visual representation of peer effects to the customers and it has the potential to act as virtual peer effects. Figure 2.2 shows an example of customer map implemented by EnergySage. It shows the number of people in the neighborhood of a Boston based customer, who has requested quotes via EnergySage.

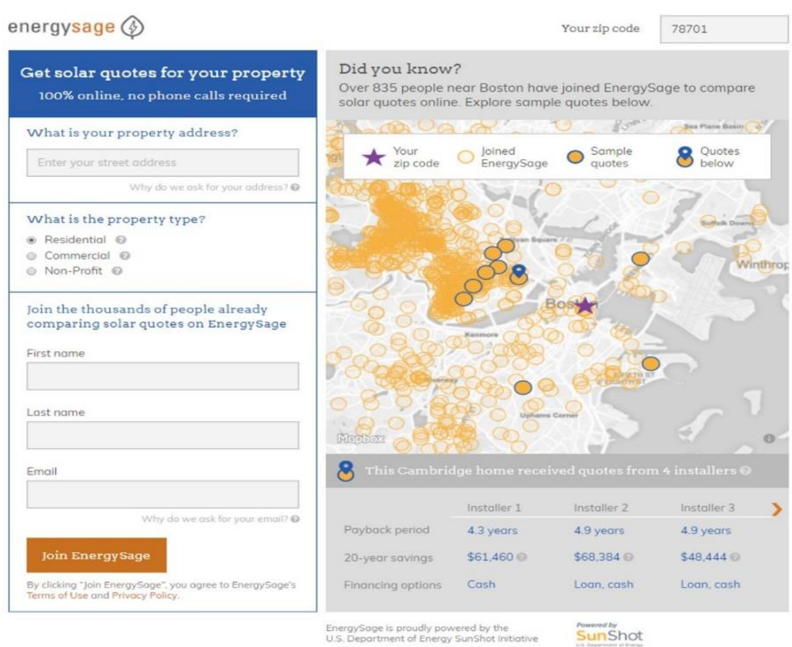

Figure 2.2. Screenshot of the customer map from EnergySage website

This new feature does not provide customers with any additional information about price expectations, but it may still empower customers to seek additional quotes and push for lower prices.

2.2.2 Quote cap

Since July 2016, a cap has been set on the maximum number of quotes that can be made for a given customer.

The effects of the quote cap, in particular, are ambiguous. EnergySage implemented the cap in response to customer and installer feedback of information overload on the platform when large numbers of installers submitted quotes to the same customer. Capping the number of quotes received could inflate prices, given findings that quote prices generally decline with the number of quotes received (O'Shaughnessy and Margolis 2017).

At the same time, the effects of the number of quotes received on prices are diminishing in strategic bidding models (Friedman 1957; Holt 1980; McAfee and McMillan 1987), such that the quote cap may not have a significant positive impact on prices and may allow customers to compare quotes more efficiently. Gilley and Karels (1981), in their study, find that individual bids decrease, i.e., they become less competitive, as the number of bidders increases. This can be attributed to bidders rationally taking into account the winner's curse and adjusting for it. The winner's curse refers to the tendency for the winner of an auction to bid higher than the actual value of object on sale. In order to win, the winner overcompensates and ends up paying higher. Thus, increasing the number of bidders above a certain number can change the effect of competition on the quote values.

Also, it may be possible that when there was no cap on the maximum allowed quotes, there were some non-serious bidders who were also submitting bids. Such bids would have been non-competitive in nature. Now, with the implementation of quote cap, one must quickly book a slot before the bids reach the cap limit. So, there is a chance that the serious bidders may be preemptive in booking their slot and being serious bidders, they might offer competitive bids.

2.2.3 Price reference

Since March 2017, a price reference has been introduced for the installers where they are provided information about competitive prices in the customer's area before submitting a quote.

The price reference change may have different impacts on the quote prices of different installers. Price reference change has the potential to act as an anchor, making the bidders offer quotes nearer to the competitive bids. Studies discuss the presence of anchoring-and-adjustment effect, while making judgements under uncertainty, which leads to an insufficient adjustment away from the anchor and makes the decision makers biased towards the anchor (Tversky and Kahneman 1974). Galinsky and Mussweiler (2001) apply the same concept of anchors to negotiations between buyer and seller. They find that first offers act as anchors and conclude that first offers act as strong predictors of final settlement prices. Since price reference acts as an indication of competitive prices, it can be considered as a first offer, and it may lead to lower quote prices by acting as an anchor.

Further, Beggs and Graddy (2009) define rational learning as the use of a relevant reference to learn an unobservable quality. Thus, price reference change may allow some above average-price installers to learn about their non-competitive quote prices, inducing these installers to offer lower prices after the change. At the same time, the price reference change may have signaled to below average-price installers that these installers could afford to mark up prices without losing customers. Thus, the net effect of the price reference change is *ex ante* ambiguous.

2.2.4 No pre-quote-messaging

Since June 2017, installer's ability to send messages to customers prior to offering a quote was removed.

The no pre-quote messaging change was likely to induce installers to offer lower prices, as the change removes the possibility of price markups from pre-quote sales tactics or value-based pricing. Ulaga and Eggert suggest that relationship benefits have a stronger potential for differentiation, than cost considerations. They suggest supplier's service support and personal interaction as core differentiators (Ulaga and Eggart 2006). Thus, pre-quote messaging may allow the suppliers to create stronger relations with customers and allow them to offer higher prices. However, the no pre-quote messaging change could negatively affect customers that are more interested in premium products, as it may be more difficult to signal a willingness to pay for premium equipment without pre-quote messaging.

The remainder of this report empirically tests the effects of the four quote platform design changes on quote prices and purchase prices.

Chapter 3: Data and Methods

In this chapter, we discuss the data made available by EnergySage and the statistical methods applied on the dataset. In section 3.1, we summarize the dataset with details on number of quotes and system characteristics contained in the dataset. In section 3.2, we explain our main regression model and the explanatory variables used in the model. Further, we explain the modifications made to the model to incorporate the four design changes.

3.1 Dataset

EnergySage, established in 2009, is an online platform for turnkey solar PV systems. It is based in Boston and is active in over 30 states. It allows customers to compare options on solar contractors through its online marketplace. EnergySage's platform takes relevant information from the customers and shows them multiple bids. The customers compare bids and select the best valued bid based on their preferences.

EnergySage provided us data on 138,183 residential PV quotes made to 42,974 customers in 36 states and Washington, DC between 2013 and third quarter (Q3) 2017 to support our analysis. The data include a rich set of system characteristics such as quote price ($/W), system size (kW), equipment used (modules, inverters), and temporal variables such as quote date. To simplify the analysis, all quotes without an up-front purchase option (N=2,631) were dropped, such that an up-front system price is available for all remaining quotes in the dataset.

Further, about 7,000 quotes containing missing values and null values were dropped. Also, there were a few quotes with a very high/ very low quote price and few quotes with system size greater than 1,000 kW. These quotes were dropped as well, since they were outliers likely due to incorrect data entry. We also leave out quotes by installers with less than 10 quotes. This is because, later in our analysis, we take installers as fixed effects using the dummy variables approach. There are more than 400 installers, with some small installers having too few quotes. Because of these small installers, taking dummy variables for each of the 400 installers yields a sparse matrix. Such a linear regression model suffers from high computation cost and high multicollinearity. So, we drop the installers with less than 10 quotes. Thus, the final analysis dataset consists of 128,009 quotes made to 41,933 customers.

EnergySage also provided an indicator variable for whether a quote was ultimately accepted by a customer. Further they provided data on over 60,000 installer *intents*, where an installer expressed interest in bidding to a given customer but did not ultimately submit a quote. Installers in the EnergySage network are able to see the number of intents before submitting a bid to a customer. Installer intents provide a key input into our regression model, described in the following subsection.

3.2 Regression Model

First, we build a preliminary model with quote price as the dependent variable. We intend to explain the quote price using a linear regression model with explanatory variables based on system related characteristics (system size, type of inverter, panel quality etc.), competition and temporal variables (quote date).

Installers, during EnergySage's bidding process, are unaware about the rival installers and the prices they quote. But, they are able to see the number of interested installers at the time of submitting their bid. The final number of installers who actually bid to a customer may be less than this initial number of installers who had shown intent. So, the installers see this number, i.e., the number of *initial intents*, when making a bid.

Thus, they perceive this number as the expected competition and react to it. We refer to this number of installer intents, as the *expected competition*.

We assume this *expected competition* to have a direct impact on quote prices. There have been a number of studies on the competition effect. The competition effect states that an increase in number of competitors leads to lower and more competitive bids (Carr 1983; Harris and Raviv 1981; McAfee and McMillan 1987). Thus, we base our assumption on the competition effect and believe that *expected competition* should have a negative effect on the prices. Further, the competition effect may not be linear. Most strategic bidding models assume that number of competitors has a non-linear effect on the quote prices (Lorentziadis 2016; McAfee and McMillan 1987; Rothkopf and Harstad 1994). They assume that moving from one installer to two installers has a greater effect on prices than moving from two installers to three. We take log transformation of *expected competition* to account for this non-linearity. Thus, natural log of *expected competition* is one of our explanatory variables.

System related explanatory variables are represented in the form of matrix X. The quote date (the date when an installer made a quote) is converted to *quarter* variable, i.e., each date is mapped to its corresponding quarter, and taken as a linear variable. We assume that quote prices should decrease nearly linearly with respect to the *quarter* in which the quote was made. To verify the same, we plot the average quote price for each *quarter*. The plot is shown in Figure 3.1 and a linear trend with negative slope is observed.

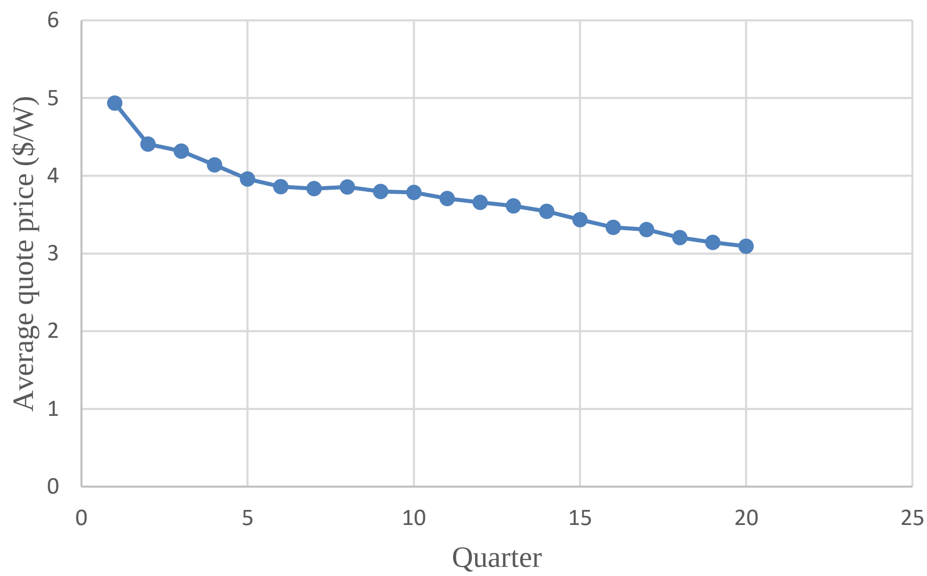

Figure 3.1: Average quote price vs. Quarter

We take *quarter* as another explanatory variable and assume that solar prices have a continuous negative trend with respect to time, and that this trend is almost linear. The following linear regression model is set up (shown in *Equation (1)*) with quote price as the dependent variable.

Equation (1) is:

$p = comp \cdot \lambda + quarter \cdot \alpha + X \cdot \beta + CTY + INST + \mathcal{E}.$

Here, p is the quote price ($/W), *comp* is natural log of expected competition, *quarter* represents the quarter of each quote date, and X is a matrix containing variables system size, system size squared, annual electricity use, dummy variables for panel rating and type of inverter. *CTY* is a county fixed effect, *INST* is an installer fixed effect and Ɛ is the error term.

λ shows the effect of doubling of competition on the quote prices, since *comp* is natural log of competition. α represents the change in quote price with an increase of one in the value of quarter. β is a vector of coefficients representing the effect on quote prices of the system related information contained in X. Let this be model (1).

Table 3.1 contains descriptions of all variables as well as summary statistics.

Variable	Units	Description	Mean/ Range
p: quote price	\$/W	The quote price per Watt being offered by a given installer	3.38
comp: expected competition	total intents (logged)	Natural log of total number of interested installers	1.60
quarter	3 months	Quarter label given to each quote date accordingly	1 to 20
CTY: county	X	Fixed effect to control for geographical differences in prices	X
INST: installer	X	Fixed effect to control for installer price differences	X
system size	kW	Control for economies of scale in system size	8.85
system size squared	kW^2	Control for diminishing return to economies of scale	297.64
annual electricity use	kWh/year	Control for value based pricing	15,418.01
panel rating	factor: economy*, standard, premium	Control for price differences based on panel cost	economy: 7,396 standard: 109,555 premium: 11,058
inverter type	factor: micro*, DC optimizer, string	Control for price differences based on inverter cost	micro: 40,426 optimizer: 71,452 string: 16,131

Table 3.1: Summary statistics and description for explanatory variables

For incorporating the county and installer fixed effects, we use the dummy variables method. We add a dummy variable for each county and each installer. These dummy variables are binary and take a value 1 for quotes from the county (or installer) represented by that dummy and take value 0 for rest of the quotes from all other counties (or installers).

Also, we drop one dummy variable for county and one dummy variable for installer to remove exact multicollinearity from our regression. Similarly, dummy variables are added for standard and premium panels with economy as the reference. Dummy variables are added for DC optimizer and string inverters with micro inverter as reference.

After setting up the linear regression, we add the four indicator variables to this regression, to gauge the effects of the four design changes made by EnergySage. We use the concept of regression discontinuity to analyze the impact of these four changes. Regression discontinuity requires addition of an indicator variable based on a running variable. The running variable has a cutoff limit above which the indicator variable takes value one and below which it takes the value zero. In our regression model, *quarter* is taken as the running variable. The dates when the design changes were implemented are taken as the cutoff limits. The indicator variables take value 0 before these cutoff dates and value 1 after the cutoff date. Table 3.2 shows distribution of quotes for the four indicator variables, before and after the design changes were made.

Variable	Quotes before design change	Quotes after design change
Customer map	25,781	102,228
Quote cap	33,345	94,664
Price reference	81,536	46,473
No pre-quote messaging	108,729	19,280

Table 3.2: Distribution of indicator variables before and after the design changes

The following modified linear regression equation is setup (shown in *Equation (2)*) with the four indicator variables to account for the four design changes.

Equation (2) is:

$p = comp \cdot \lambda + quarter \cdot \alpha + X \cdot \beta + customer\ map \cdot \beta^{cm} + quote\ cap \cdot \beta^{qc} + price\ reference \cdot \beta^{p} + no\ pre\text{-}quote\ messaging \cdot \beta^{pm} + CTY + INST + \mathcal{E}$.

The coefficients of the indicator variables reflect the impact of these design changes on quote prices. Let this be model (2).

Up to this point, we take the complete dataset with all quotes and run our regression model. The objective here was to analyze the installer based strategies as the competition and other factors change and as various design changes are brought into effect in the auction process. Thus, since our focus is on quote prices and how the installers adjust their quote prices in different auction settings, we apply our regression model to the full sample of quotes provided by installers to customers.

After analyzing the quote prices in models (1) and (2), we restrict the dataset to only the accepted quotes, i.e., the winning quotes offered by the installers which were finally accepted by customers. We run the same regressions, on this restricted dataset (let the corresponding new models be (3) and (4)). Model (3) is analogous to model (1), i.e., it does not include the platform design change indicators and model (4) is analogous to model (2), i.e., it does include the design change indictors. We restrict our dataset to understand how the customers actually value the system characteristics with specific focus on panel quality. There is a general concern that online auctioning of solar PV may lead to deteriorating quality of equipment being offered. The reason is that customers may place too much emphasis on price and this may result in a race to the bottom, where quality is neglected. Thus, to assess this concern we focus on panel quality.

Thus, repeating the same regression on both datasets enables us to directly compare how the installers price standard and premium panels (from all quotes dataset) and how much the customers are willing to pay for the standard and premium panels (from the accepted quotes dataset). Also, we can compare the effect of competition between all the quotes available in the market and the quotes that actually go on to win the bid.

As discussed, we specifically focus on the coefficients related to panel quality and competition in models (3) and (4) and see if their values change significantly from that of the same coefficients for models (1) and (2).

Chapter 4: Results

In this chapter, we discuss the results for the regressions presented in section 3.2. In section 4.1, we discuss the basic results, where we show the effect of competition, time and panel quality on the quote prices. In section 4.2, we discuss the impact of the four design changes on quote prices offered by the installers and provide an additional robustness check for our model. In section 4.3, we focus on valuation of panel quality and see if the customers are sacrificing quality in favor of lower prices.

4.1 BASIC RESULTS

Table 4.1 shows the results for the four regressions. The first column, i.e., regression (1), shows results for the basic linear regression without including any of the design changes. This model is to show the robustness of results with respect to the impact of *system size*, *quarter* and *expected competition* on the quote prices. As shown, the coefficients for these explanatory variables are very similar between the basic model and the modified model with all design changes included. Thus, the analysis is robust to design changes, i.e., the effect of the mentioned variables on quote price is well explained by our model.

Further, we can analyze the effect of these variables on quote prices. The *comp* variable is natural log of the *expected competition*; thus, we can interpret its coefficient as the effect of doubling of competitors on the quote price. It has coefficient -0.022 in the basic model and coefficient -0.0388 in the final model, i.e., regression (2) of Table 4.1. This means that as the competition is doubled the quote price goes down almost by 0.04 $/W. Thus, installers offer lower prices when expecting more competition. So, the competition effect discussed in section 2.2 can be clearly seen in action here. Our results are consistent with O'Shaughnessy and Margolis's (2017) results. They set up a similar model and run it on the same EnergySage dataset, with data until December 2016.

Also, *quarter* variable's coefficient shows that quote prices are decreasing by almost 6 cents per watt every quarter. Thus, our results are in line with the decreasing trend observed in Figure 3.1. There is a continuous reduction in solar PV installation prices for last few years. Similarly, standard and premium panels, as expected, have a positive effect on the quote prices. Standard panels tend to cost around 0.04 $/W more than the economy panels, whereas, premium panels tend to cost around 0.48 $/W more than the economy panels. This high difference between standard and premium panel prices also explains why most quotes given by the installers are for the standard panel. Of the 128,009 quotes, only 11,058 quotes are for premium panels, whereas over 100,000 quotes are for standard panels. Thus, premium panels, which necessitate a higher quote price, are a niche market with fewer customers demanding them and correspondingly fewer installers offering them.

Variable	(1) All quotes, no design changes	(2) All quotes, all design changes	(3) Accepted quotes, no design changes	(4) Accepted quotes, all design change
expected competition (logged)	-0.022 (7.1)*	-0.039 (12.2)*	-0.103 (-4.0)*	-0.110 (4.3)*
sys size	-0.001 (57.9)*	-0.001 (58.3)*	-0.029 (9.3)*	-0.029 (9.4)*
sys size^2	1.089e-05 (42.7)*	1.089e-05 (42.9)*	4.362e-05 (9.4)*	4.426e-05 (9.6)*
annual elec. use	4.202e-08 (2.6)*	4.639e-08 (2.9)	2.075e-06 (1.6)	1.866e-06 (1.5)
standard panel	0.043 (7.6)*	0.044 (7.8)*	0.069 (1.5)	0.063 (1.4)
premium panel	0.488 (68.4)*	0.503 (70.8)*	0.605 (11.3)*	0.621 (11.6)*
DC optimizer inverter	-0.037 (9.8)*	-0.037 (10.0)*	-0.059 (2.0)**	-0.060 (2.0)**
string inverter	-0.064 (12.8)*	-0.047 (9.3)*	-0.115 (3.2)*	-0.088 (2.4)**
quarter	-0.069 (125.8)*	-0.042 (40.1)*	-0.061 (14.9)*	-0.036 (9.63)*
customer map	-	-0.035 (6.0)*	-	-0.075 (1.7)
quote cap	-	-0.054 (10.6)*	-	0.001 (0.3)
price reference	-	-0.104 (28.4)*	-	-0.148 (4.9)*
no pre-quote messaging	-	-0.052 (13.2)*	-	-0.058 (1.5)
County	X	X	X	X
Installer	X	X	X	X
Intercept	5.222 (13.8)*	4.780 (12.7)*	4.826 (17.2)*	4.514 (15.78)*
R^2	0.52	0.53	0.67	0.68

Y=price ($/W), t-statistics in parentheses

Table 4.1: Regression results

Note:
* Statistically significant at $p<0.01$
** Statistically significant at $p<0.05$

4.2 Design Changes

Column (2) of Table 4.1 shows the results for modified model with the four design changes included. Apart from the explanatory variables in the basic model, we have four indicator variables for each of the four design changes. We discuss the results for each of these design changes below.

4.2.1 Customer map

Customer map, as discussed, may not provide customers with direct changes in prices. But, it may lead to lower prices by encouraging customers to push for more quotes. Also, it may lead to a virtual peer effect, with customers trying to seek out true market prices or customers trying to find out their peers and become more informed. We observe a negative coefficient for *customer map* (however, this is not as statistically significant as the other indicators), showing that virtual peer effect is in action. Also, it is possible that the map feature may convince new customers, who would otherwise not be inclined, to request a quote. Possibly, such customers place lower value on solar PV and demand lower prices.

4.2.2 Quote cap

In July 2016, EnergySage decided to put a cap of 7 on number of quotes allowed per customer. The major reason behind this was the feedback received from customers, about information overload. Seeing too many bids can actually confuse the customers and make it difficult to analyze the best possible bid. The coefficient for *quote cap* comes out to be negative with reduction in quote prices by 0.05 $/W.

It seems possible that with no cap in place, many installers could be putting in bids just for the sake of participation. These bids would not be competitive in nature. Whereas, with a cap in place, the serious bidders would make a prompt effort to bid and come up with competitive bids. Our interpretation is validated by the regression results of column (4), i.e. when we regress on just the purchased quotes. The coefficient for *quote cap* is almost zero here and it is not statistically significant. This means, the quote cap has no significant effect on the actual winning quote prices. Assuming that only serious bidders would go on to win the bids, our interpretation of the results seems plausible.

4.2.3 Price reference

Price reference has the most prominent effect on quote prices, and it is the most significant (in terms of p-value of the coefficient). This is expected, since this design change directly guides the installers rather than guiding customers and indirectly affecting prices. As discussed in section 2.2, studies have been conducted on anchoring effects, but these have mainly been on consumer side. We see the same anchoring effect in action on installer's side as well, with installers moving towards more competitive bids. The decrease of 0.10 \$/W for the coefficient of *price reference* suggests that after the implementation of this design change, installers have reduced their quote prices and have submitted more competitive bids. Thus, they have realized that the customers are going for lower priced quotes and to stay competitive they need to reduce their mark up. Moreover, installers also tend to believe that their competitors will offer a similar price, since they see the same reference. This should again make them offer more competitive quotes. This suggests that the price reference is the most impactful design change, guiding the installers to quote a lower price.

4.2.4 No pre-quote messaging

As discussed in section 2.2, disallowing the pre-quote messaging feature may lower the prices. The same can be seen in the results in column (2). The coefficient of indicator variable for *no pre-quote messaging* is negative, indicating that this design change led to lowering of prices. As discussed, removing the ability to message the customers prior to making quotes should reduce the personal interaction between installers and customers, which would have allowed the installers to gauge the customer's willingness to pay a higher price and would have allowed them to charge value based pricing from the customers. Thus, it appears that stopping this messaging feature reduces the chances of installers marking up a higher price. It can be interpreted that the installers might thus be discouraged from using value based pricing and from using pre-quote sales tactics.

4.2.5 Robustness checks

It is to be noted that in creating indictor variables for the four design changes, we are also splitting the data into two categories: old quotes and new quotes. This means that there is an inherent temporal nature attached with the indicator variables. Also, we have assumed the quote prices to be linear based on the trend observed in Figure 3.1 and taken *quarter* as a linear variable. But, it may be the case that there are some unobserved temporal effects, which remain unexplained by this linear *quarter* variable. In that case, these four coefficients of design changes may not purely reflect the design changes, but may include an element of temporal changes in prices. Thus, it may happen that a certain proportion of the coefficients of these indicator variables may be due to temporal effects.

So, it is necessary to verify the robustness of our results. To do this, we restrict the data to two months prior to and two months after these design changes, i.e. around the points of discontinuity. The reason being that the quote prices won't change a lot in just four months, as compared to change in quote prices over three years. We do this individually for each of the design change.

For example, the *price reference* change was brought into effect on 3rd March 2017. So, we restrict the data from 3rd January 2017 to 3rd May 2017, i.e., two months before and after the design change. Now, we run the same regression which is mentioned in Equation (2) (but, we keep only the indicator variable for price reference, since other indicator variables are constant in this time period). In our results, we still find a negative coefficient for price reference and it is statistically significant (shown in Table 4.2). We observe comparable results for the other design changes, except customer map, which is no longer statistically significant. Table 4.2 shows the coefficients for the four indicators, when restricted to 4 months.

Design change	Coefficient of corresponding indicator variable	t-statistic
Customer map	-0.001	0.9
Quote cap	-0.038	5.0*
Price reference	-0.028	2.8**
No pre-quote messaging	-0.032	5.5*

Here, we restrict the dataset to just 4 months around the point of discontinuity for each design change (2 months before and after the design change) and run the same regression as specified by equation (2)

Table 4.2: Robustness check of coefficients of indicator variables

Note:
* Statistically significant at $p<0.01$
** Statistically significant at $p<0.05$

4.3 Valuation of panel quality

The results for regression models (3) and (4) (i.e., on the restricted dataset) are shown in columns (3) and (4) of Table 4.1. As shown, the coefficients for standard panel and premium panels increase in case of purchased quotes when compared to the same coefficients in case of complete dataset with all quotes, i.e., columns (1) and (2). The coefficient for *standard panel* goes up marginally to 0.06, whereas *premium panel* coefficient goes up considerably, to 0.60. Thus, we can say that the customers who make a purchase are ready to pay higher for a premium panel than the amount being quoted by an average installer.

Thus, the customers value the premium panels more and there is a scope for installers to have a higher price markup, when it comes to premium panels. Also, it may be the case that installers offering premium panels realize that they are in a niche market and thus know that the customers will be more willing to pay a higher price for a quality product. Thus, these installers may be putting in more efforts to close the deal, by increasing personal interaction with the customers and following up more frequently with the customers via messaging services provided by EnergySage. Also, this is very encouraging from the platform perspective, since the overall platform design is not encouraging a race to the bottom, where customers prefer lower prices at the cost of quality. On the contrary, we find that customers value the premium panels more than what the installers are expecting, since the installers are quoting premium panels at relatively lower prices than what the customers are willing to pay.

Another interesting observation is the change in the coefficient of *comp* in the regressions (3) and (4), when compared to that in regressions (1) and (2). The coefficient takes the value around -0.1, when the data is restricted to just the accepted quotes. This is significantly lower than -0.039, for all quotes. Thus, the competition effect is far stronger in accepted quotes than in all quotes made by the installers. While installers are reducing prices by 0.04 $/W for doubling of competition overall, the winning quotes see reduction of prices by 0.10 $/W for each doubling of competition. So, it can be said that, on an average the installers making winning bids are willing to offer prices a lot lower than their competition and this willingness increases with an increase in competition.

We also look at the spread of quotes based on the panel quality. Of the 128,009 quotes, only 11,058 quotes are for premium panels and 7,396 quotes are for economy panels, whereas over 109,555 quotes are for standard panels. As discussed earlier, customers have an option to choose between performance and cost, while requesting for a quote. They do so by specifying if they prefer a system with most advanced technology or if they prefer a system with best economic value. We observe that cost of moving from economy to standard panels is marginal (4 cents per Watt, column (2) of Table 4.1), whereas marginal cost of moving from standard panels to premium panels is comparatively more (48 cents per Watt, column 2 of Table 4.1). Thus, we find more than 80 percent of the quotes to be for standard panels. While, premium panels, which necessitate a higher quote price, are a niche market with fewer customers expressing interest in them up front and correspondingly less number of installers dealing in them.

Chapter 5: Discussion and Conclusion

Quote aggregator platforms hold a unique importance in the diffusion of solar PV technology. The solar PV industry has a relatively non-transparent market and the customers who are still in the early stages of adoption struggle to get proper information. In this scenario, quote aggregator platforms like EnergySage help in informing the customers about better prices, new technology and solar PV adoption status in their neighborhood. With multiple quotes on offer to the customers, the competition effect is in action and the installers are forced to lower the prices, thus aiding the process of creating a more transparent market. Similar to results by O'Shaughnessy and Margolis (2017), we find that doubling of the number of quotes reduces the quote prices by $0.04/ Watt. This effect is even stronger when we restrict the data to accepted quotes. It shows that installers who win bids show more willingness to offer lower prices with increase in competition.

The quote prices show a linear downward trend with respect to time. The same can be seen in Figure 3.1. Our regression results confirm the same and show a four to six cents reduction in prices per watt ($/W) in each quarter. With more people adopting solar PV and with stronger efforts from policy makers to incentivize solar PV industry, the solar PV market has grown exponentially in the last few years. Thus, factors like economies of scale and learning-by-doing effects have aided this steep reduction in solar PV prices and continue to result in lower prices.

The major findings of our research are related to the design changes introduced by EnergySage to their bidding process. Introduction of no pre-quote messaging and customer map reduce the prices. As discussed, taking away the ability to make personal interactions with the customers before making a quote, reduces the chances of installers using value based pricing strategies, thus resulting in reduced prices.

Customer map is an interesting feature introduced by EnergySage as it provides a visual representation of the peer effects. The customers visualize the number of people around them who have shown interest in the quote aggregator's platform. This should act as a virtual peer effect and aid the final adoption rates. Customer map should aid customers in realizing the solar PV market size in their neighborhood. Also, it may push the customers to be more informed and actively seek more quotes from installers, thus lowering the quote prices.

This has an important policy implication. The policy makers should use the concept of virtual peer effects and come up with innovative methods to spread awareness about the current solar PV adoption status. Virtual peer effects can act similar to peer effects without needing any actual personal communication with the peers. They help consumers get a sense of their surroundings with visualization tools like maps, which go beyond just statistics and numbers. Thus, the policy makers should educate the consumers about localized adoption rates using virtual visualization tools.

The quote cap gives mixed results with a negative coefficient for complete dataset and a near zero coefficient for the dataset restricted to accepted quotes. The negative coefficient suggests that putting a cap on the number of installers has reduced the quote price. As discussed, this result can be attributed to winner's curse. With an increase in number of bidders, there is increased prevalence of winner's curse (wherein the winner over compensates and ends up paying higher than the true value of the object in auction). Thus, assuming the installers act rationally, they may have been compensating for this winner's curse and quoting a higher price when the cap was not in action.

Another possible interpretation is specific to our case. It may be the case that earlier, with no limit on the number of bids per customer, there were some installers putting in non-competitive bids. Now, with a cap on the maximum allowed bids, competitive bidders are prompt in booking their slot, and thus more competitive bids make it to the customers, leading to reduction in quote price.

Introduction of price reference, providing the installers with information about more competitive bids in the market, is the most significant change. This is expected, because this change directly impacts the quote prices by guiding the installers. The coefficient of -0.104 suggests a strong negative impact on prices with the introduction of this change. There are couple of things in action here, one is the anchoring effect of price reference, making the installers move towards more competitive effect. Also, there is an element of rational learning, since the installers are now able to better estimate the winning quotes because of price references provided to them. Thus, they gradually reduce their prices to offer more competitive bids.

This has important policy implications, since most of the efforts on increasing solar PV transparency and reducing solar PV pricing are based on making the customers more aware about the market and better informing the customers about solar PV prices. But, an increased focus on the installer's side, by making them realize current competitive prices in the market and disseminating information on factors that lead to more competitive bids, can greatly impact the solar PV prices.

There are a couple of future research directions in which our work can be extended. One, is to look at conversion ratios in each step, starting from (1) initial interest for solar PV in market, to (2) the total number of people who manage to end up on quote aggregator platforms to (3) the number of people who demand for quotes and finally ending with (4) the number of people who actually accept the quotes. If a way of quantifying the current interest in solar market can be established, we can study the initial conversion rate of this *potential interest* into *footfalls* on quote aggregator platform. Also, if we can get data on website traffic on EnergySage's platform, we can see how the conversion ratio of *web traffic* to *quotes demanded* has changed over time with the introduction of these design changes.

Second, given a customer profile it will be interesting to come up with probability of adoption for that customer. Customer profile may include their income, location, age, financial incentives available to them etc. This can immensely aid the quote aggregators and the policy makers in classifying the people into two buckets, likely adopters and unlikely adopters. They can thus analyze the policy changes that can be brought into effect to incentivize solar PV adoption.

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